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Machine learning for fault diagnosis in electrical systems: systematic review of applications and trends

Aprendizaje automático para diagnóstico de fallas en sistemas eléctricos: revisión sistemática de aplicaciones y tendencias

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ABSTRACT

Introduction: Fault diagnosis is essential for the safe and reliable operation of electrical power systems, while machine learning has become a central approach for automating detection, classification and localization tasks.
Objective: This review identifies and synthesizes applications and methodological trends reported between 2019 and 2022.
Method: A structured literature review was conducted in Scopus, Web of Science, PubMed and SciELO, using explicit eligibility criteria and a narrative thematic synthesis. Thirty-five publications formed the final corpus. The review was guided by PRISMA 2020 reporting principles; however, intermediate screening counts were not retrospectively reconstructed because they had not been recorded during the original search.
Results: The evidence shows a transition from support vector machines, artificial neural networks and other shallow-learning methods toward convolutional and recurrent deep-learning architectures. Power transformers, transmission lines and distribution networks were the most developed application domains. Transfer learning, hybrid models, multisensor diagnosis, interpretability and cybersecurity emerged as relevant research directions. Reported accuracies were high in several selected studies, but comparisons are limited by heterogeneous datasets, signals, validation protocols and metrics, and much of the evidence derives from laboratory, simulation or benchmark settings.
Conclusions: Machine learning has substantial diagnostic potential, but industrial adoption requires external validation, standardized evaluation, transparent reporting, robust data governance and stronger evidence under real, variable and operationally demanding conditions across different electrical assets.

Keywords: machine learning; deep learning; fault diagnosis; electrical power systems; systematic review

RESUMEN

Introducción: El diagnóstico de fallas es esencial para la operación segura y confiable de los sistemas eléctricos, mientras el aprendizaje automático se ha convertido en un enfoque central para automatizar tareas de detección, clasificación y localización.
Objetivo: Esta revisión identifica y sintetiza las aplicaciones y tendencias metodológicas publicadas entre 2019 y 2022.
Metodología: Se realizó una revisión estructurada en Scopus, Web of Science, PubMed y SciELO, con criterios explícitos de elegibilidad y síntesis narrativa temática. El corpus final estuvo constituido por 35 publicaciones.

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El reporte se orientó por PRISMA 2020; sin embargo, no se reconstruyeron retrospectivamente cifras intermedias de cribado porque no fueron registradas durante la búsqueda original.
Resultados: La evidencia muestra una transición desde máquinas de vectores de soporte, redes neuronales artificiales y otros métodos superficiales hacia arquitecturas profundas convolucionales y recurrentes. Los transformadores, líneas de transmisión y redes de distribución concentraron las aplicaciones. El aprendizaje por transferencia, los modelos híbridos, el diagnóstico multisensor, la interpretabilidad y la ciberseguridad emergieron como tendencias relevantes. Las precisiones fueron elevadas en varios estudios seleccionados, aunque la comparación está limitada por la heterogeneidad de datos, señales, protocolos y métricas, y por el predominio de validaciones controladas.
Conclusiones: El aprendizaje automático posee alto potencial diagnóstico, pero su adopción industrial requiere validación externa, evaluación estandarizada, reporte transparente, gobernanza robusta de datos y evidencia en condiciones reales.

Palabras clave: aprendizaje automático; aprendizaje profundo; diagnóstico de fallas; sistemas eléctricos; revisión sistemática

INTRODUCTION

Electrical power systems are the infrastructure on which the functioning of contemporary societies is sustained, and their safe operation depends on the ability to detect, classify and locate faults quickly and accurately. Power system failures can occur anytime, anywhere, can be caused by natural disasters or accidents, and their occurrence can hardly be predicted or avoided, so it is crucial to accurately estimate the location of the fault and restore service quickly, and the development of methods capable of accurately detecting, locating and eliminating faults is essential to maintain system stability and to increase reliability and consumer satisfaction (1). Components of electrical systems are susceptible to failure due to atmospheric discharge, aging or human error, and these failures can cause damage to equipment, affect system reliability and generate high repair costs, while the evolution of the traditional system towards the smart grid has modified the way power systems are operated and protected and has increased the demand for advanced diagnostic techniques (1).

Faced with this need, conventional methods of protection and diagnosis, based on mathematical models and signal processing, have shown increasing limitations. Fault recognition and classification using traditional methods presupposes the application of mathematical models and signal processing techniques that are ineffective in identifying and categorizing defects in complex power systems (1). In the broader industrial arena, intelligent fault diagnosis, defined as the application of machine learning theories to machine failure diagnosis, is a promising avenue for unlocking the contribution of human labor and automatically recognizing the health states of machines, and has attracted considerable attention over the past two to three decades, although a review that would systematically cover its development from inception to flourishing and provide potential guidelines for its future development was lacking (2).

The advent of deep learning has reshaped the field particularly intensively. Deep architectures, which exploit multiple hidden layers to automatically learn hierarchical representations from big data, present a promising tool for characterizing fault conditions (3). The review by Saufi et al. recalled that, in the era of Industry 4.0, deep learning models have been extensively implemented in machinery fault detection and diagnosis systems, and that the automated process of feature learning offers great

potential to solve the problems of traditional systems, which rely on manual feature selection and require prior knowledge of the data (4). These capabilities have found fertile ground in electrical engineering, where voltage and current magnitudes, vibration signals, partial discharges, and data from monitoring systems are natural inputs for learning models.

The scientific output from 2019 to 2022 reflects this confluence between the maturity of algorithms and the increasing availability of monitoring data, and has given rise to an abundant but dispersed literature, focused on specific domains transformers, lines, distribution networks, converters, rotating machines, wind turbines, photovoltaic systems and in particular algorithmic families support vector machines, convolutional neural networks, recurrent networks, transfer learning. The available syntheses frequently address a single domain or a single algorithmic family, and lack a cross-sectional integration that would allow identifying consolidated applications, emerging trends, and persistent gaps in the field as a whole.

Based on the scientific production from 2019 to 2022, the present research set out to systematically examine the evidence on the applications and trends of machine learning in the diagnosis of electrical system failures. The research question guiding the study is the following: what are the application domains, algorithmic families, performance outcomes and trends documented in the literature published between 2019 and 2022 on the diagnosis of faults in electrical systems using machine learning, and what are the remaining challenges and future directions of the field? Given the descriptive and synthesis nature of the design, a statistical verification hypothesis is not formulated, but a working proposition: it is anticipated that the corpus will document the increasing predominance of deep learning architectures over surface methods, the concentration of applications in the most critical transformer equipment, distribution lines and networks, the emergence of transfer learning and hybrid models as dominant trends, and the persistence of challenges related to data availability, generalizability and interpretability of models.

LITERATURE REVIEW

From conventional diagnostics to smart diagnostics

The diagnosis of faults in electrical systems has gone through three recognizable stages. The first, of a conventional nature, was supported by analytical models of the system and signal processing, with techniques such as impedance estimation, traveling wave analysis, and inspection of voltage and current waveforms (1). These methods have structural limitations: they depend on the accuracy of the model, the experience of the operators, and the quality of the measurements, and their performance degrades in the face of the increasing complexity of the networks, the penetration of distributed generators, and the variability of operating conditions. The second stage, of intelligent diagnostics, incorporated the theories of machine learning to weaken the contribution of human labor and usher in the era of artificial intelligence in fault diagnosis, and the third stage, driven by the advent of deep learning theories since the 2010s, reformed intelligent diagnostics by encouraging the construction of an end-to-end diagnostic process that directly links monitoring data with the health states of equipment (2). The review and roadmap by Lei et al. warned that, in the future, transfer learning theories will attempt to use diagnostic knowledge from one or multiple tasks for other

related tasks, which will prospectively overcome the obstacles of applying intelligent diagnostics in engineering scenarios (2).

These general trajectories are manifested in a specific way in electrical engineering. Transmission system classification and fault location techniques predominantly use artificial intelligence and signal processing methods, and the widespread strengths and weaknesses of different artificial intelligence and machine learning algorithms have been benchmarked (1). In the protection of transmission systems, data-driven diagnostics have benefited from the availability of synchronised measurements of phasor measurement units, which enable real-time monitoring and automated diagnosis of protective equipment failures, even in the presence of multiple adverse events and data anomalies (5).

Fundamentals of Machine Learning Applied to Fault Diagnosis

Machine learning applied to fault diagnosis is structured around a sequence of stages: data acquisition, feature extraction, feature selection, classification model construction, and performance evaluation. Feature extraction is at the core of the intelligence stage: relevant features, obtained in the time, frequency, or time-frequency domain, allow fault signals to be characterized and high-quality inputs to classification algorithms to be provided (6). Classical surface methods, support vector machines, random forests, decision trees, and artificial neural networks have a generalizability and adaptive capacity that has made them essential tools for fault diagnosis of power systems, while traditional artificial intelligence methods, such as expert systems and Bayesian networks, retain unique advantages in the explainability and transparency of decision logic (6). This transition, documented in the synthesis literature, shows that superficial algorithms have gradually replaced traditional methods as essential tools in the field of diagnosis and decision analysis of power systems (6).

Methodologically, the review by Lei et al. distinguished three generations of methods in intelligent fault diagnosis: classical artificial neural networks, which initiated diagnostic automation; deep learning methods, which reshaped diagnosis using end-to-end models; and transfer learning methods, which are the current frontier (2). This periodization is consistent with that documented by Zhao et al., whose open-source benchmark study systematically evaluated deep learning algorithms for intelligent diagnosis of rotating machinery and underlined that traditional smart diagnostic methods, based on feature extraction through signal processing and fault classification using machine learning, rely heavily on prior knowledge and are laborious and empirical in the face of heterogeneous big data (6).

Deep Learning Architectures

Deep learning architectures constitute the main vector of the evolution of the field. Tang et al.'s review of deep learning-based intelligent diagnostic methods for rotating machinery highlighted that deep learning achieves desirable machine learning of fault characteristics and classification, and systematized applications to bearings, gears, gearboxes, and pumps, along with future challenges and directions (7). Among architectures, the convolutional neural network has aroused particular interest for its advantages in processing nonlinear problems: the dedicated review by Tang, Yuan, and Zhu

introduced the basic structure and principle of the convolutional neural network, summarized and analyzed its applications to the fault diagnosis of rotating machinery, and discussed the diagnostic performance and potential mechanisms of different methods based on convolutional networks, as well as highlighting the challenges and key points of research (8). Convolutional networks also have the ability to learn features directly from raw monitoring data without preprocessing, because they capture displacement-dependent data properties, and reduce the number of training parameters through weight-sharing, thereby accelerating convergence and containing overfitting (2).

Recurrent networks, in particular networks with long-term and short-term memory, have addressed the temporal dimension of diagnosis. The long-term memory network, by integrating the temporal information of the signals, has demonstrated capacity for fault diagnosis in multilevel modular converters, where the short-time wavelet entropy extracts the fault information and the network processes that information in the temporal dimension before adaptive classification by the support vector machine (9). In wind turbine monitoring, the hybrid approach that integrates the long-term memory network with the Kullback-Leibler divergence has demonstrated more effective detection, with accuracies reaching 94% and 92% in two turbines with gearbox bearing and generator winding failures respectively (10).

Applications in power transformers

The power transformer is one of the most abundant and expensive components of the electrical industry, and its diagnosis has concentrated a considerable portion of the research of the period. The analysis of dissolved gases in oil is the most widely accepted diagnostic tool worldwide to understand incipient insulation failures, and its interpretation represents a significant challenge for transformer owners and for engineers in utility companies (11). Computational techniques have been adopted for the classification of failures by dissolved gas analysis, although the limited availability of data, the high ambiguity of interpretation and the accuracy of the models are critical challenges: the work of Rao et al., developed with 4,580 dissolved gas analysis samples from in-service transformer fleets from five utilities and with the IEC TC 10 database for the training and testing of several machine learning algorithms, concluded that nonparametric methods and the nonlinear support vector machine are the most suitable for the classification of failures by dissolved gas analysis, and that prediction is improved by ensemble learning methods (11).

In the same vein, Taha and Mansour's proposal introduced a novel diagnosis of transformer failures based on dissolved gas analysis through data transformation and six optimized machine learning methods – decision tree, discriminant analysis, Naïve Bayes, support vector machines, nearest neighbors and ensemble classification, worked with 542 samples, of which 361 were used for training and 181 for testing, and demonstrated a predictive accuracy superior to that of conventional and artificial intelligence methods (12). The combination of the nearest neighbor algorithm with the decision tree principle, developed by Kherif et al. with 501 samples, achieved an overall accuracy rate of over 93 % for the diagnosis of power transformers (13).

Beyond dissolved gas analysis, vibration measurement has opened up a complementary front. Winding condition assessment using vibration analysis provides a low-cost and non-intrusive

approach: Hong et al.'s proposal converts vibration monitoring data with load information into a vibration image and employs a convolutional neural network to classify the images, with a field experiment on more than 100 operating transformers divided into normal, degraded and anomalous categories, which achieved an overall accuracy of 98.3% and outperformed artificial neural networks, support vector machines and the Naïve Bayes classifier (14). The recognition of transformer surface vibration signals using convolutional neural networks, which integrates feature extraction and classification recognition in the same process, achieved an accuracy of 92.74% (15). In terms of protection, the denoising-classification neural network, which integrates a convolutional autoencoder and a convolutional neural network, has been proposed to develop a reliable transformer protection scheme by identifying the excitation differential voltage-current curve, which allows distinguishing between the healthy and faulty state of the transformer and improves generalization by reducing the requirement of data ergodicity (16).

Transmission Line and Distribution Network Applications

Transmission lines and distribution networks are the domains where fault localization has the most immediate operational impact. Fault line localization in large-scale power systems has been addressed by convolutional neural networks from phased measurement unit data, with methods for real-time localization and for optimal unit placement (17). In distribution networks, fault localization has leveraged machine learning models and smart meter data: Chen et al.'s review documented that smart meter data serve as input from a multi-label support vector machine to identify faulted lines, that spectral characteristics of post-failure measurements are fed to an artificial neural network for localization, and that the implementation of advanced measurement infrastructure, phased micro measurement units, and wireless sensor networks improves data-driven situational awareness of distribution systems (18). The development of a fault classification algorithm using support vector machines for smart distribution networks, which uses the current and voltage data collected by the smart meter, was one of the early applications of the period (19).

The location of faults in distribution networks with distributed generation has required robust methods against the stochasticity of fault characteristics. The proposal by Mirshekali et al. uses only the voltages recorded in the substation and in the distributed generators during the fault, selects the frequency component of the voltage signals as the characteristic vector, uses the feature selection algorithm by neighborhood components to extract the most informative characteristics and reduce the dimension, and applies a support vector machine classifier to the training data of reduced dimension, with simulations of various types of faults in a standard 11-node IEEE feeder equipped with three distributed generators (20). In microgrids, intelligent fault detection based on local measurements and machine learning techniques has allowed each smart electronic device to autonomously determine the occurrence of a fault, eliminating the requirement for robust communication infrastructure between devices for microgrid protection, and its validation on the 13-node IEEE modified test feeder, with consideration of load imbalance, reconfiguration, and offline and online modes of operation, demonstrated the flexibility and simplicity of the system to determine the best accuracy performance among various machine learning models (21).

Applications in power electronics converters and HVDC systems

The penetration of power electronics converters has shifted fault diagnosis to modular multi-level converters and high-voltage direct current systems. The detection and classification of open-circuit faults of modular multilevel converters has been addressed using deep learning methods, convolutional neural networks, and deep neural networks based on autoencoders together with the SoftMax classifier, directly using the three-phase currents of the alternating current side and the currents of the upper and lower bridges, without explicit extraction of characteristics or selection of subassemblies, with the two-terminal system implemented in PSCAD/EMTDC to verify and compare the methods (22). The combination of short-time wavelet entropy with the long-term memory network and the supporting vector machine demonstrated better robustness, adaptability and accuracy in fault diagnosis of modular multilevel converters, and allowed to considerably reduce the number of electrical signal samples and diagnose multiple types of faults by collecting a single signal (9). The intelligent diagnostic framework integrating principal component analysis for feature extraction with the multi-class support vector machine and multinomial logistic regression for classification validated its effectiveness in a two-terminal simulation model of the high-voltage DC system based on multi-level modular converters (23).

Applications in Rotating Electric Machines

The diagnosis of rotating electrical machines, in particular the induction motor, has been a privileged test bed of deep architectures. The multi-frequency diagnostic method based on a deep convolutional neural network, which learns from multiple types of sensor signals simultaneously by converting the acquired signals into time-frequency distributions using the wavelet transform and applying a deep convolutional neural network to learn discriminative representations, demonstrated a more accurate and stable performance than traditional methods in induction motor fault recognition, and overcame the problem of overfitting to some extent (3). The detection and classification of stator winding faults with convolutional neural networks based directly on the raw stator current data demonstrated the possibility of using the network in a real-time diagnostic system, with high accuracy in the incipient detection of stator winding faults for different load pairs and supply voltage frequencies (24). The wavelet core-based convolutional neural network, applied to the early diagnosis of simultaneous failures of turns in different phases of the stator winding, eliminated the requirement for feature extraction and the separate classification algorithm and showed promising results when signals are contaminated with noise (25).

Applications in renewable energy systems

The expansion of renewable energy has brought wind turbines and photovoltaic systems into the realm of automatic fault diagnosis. In wind turbines, the detection and fault diagnosis of a floating turbine's blade pitch control system has been addressed using Kalman filters and artificial neural networks, methods capable of learning how to diagnose faults from a set of training measurement datasets and detecting changes in trends (26). Monitoring of turbines in operation using the long-term memory network integrated with the Kullback-Leibler divergence demonstrated more effective detection than three well-established machine learning algorithms, with accuracy of 94% and 92%

for two failed turbines respectively, and the ability to distinguish alarms from failures, considering the distinguished alarms as an early warning of failure occurrence (10).

In PV systems, fault detection and diagnosis are a key factor for the efficiency of grid-connected systems, and their performance depends mainly on the quality of the features extracted, including real-time changes, phase changes, trend changes, and fault modes (27). Li et al.'s review of the application of artificial neural networks to PV fault detection and diagnosis documented that power loss in the UK can reach 18.9% in one year, mainly due to sustained inverter failure and shading, and systematized PV plant health monitoring strategies, from visual inspection to automatic fault analysis based on statistical methods and machine learning technology (28). Mansouri et al.'s extensive review of deep learning-based fault diagnosis methods for PV systems analyzed the strategies, differences, advantages, and limits of the proposed techniques and discussed future research directions toward improving the performance of deep diagnostic techniques (27).

Applications in electrical insulation and partial discharge

The diagnosis of the insulation of high-voltage equipment has integrated the recognition of partial discharge patterns. The recognition of partial discharge patterns of high-voltage cables was addressed using a deep learning methodology based on a convolutional neural network, in a context where traditional machine learning methods decision trees, backward propagation neural networks, support vector machines, and approximate set theory had reached bottlenecks in their development that restricted subsequent improvements in pattern recognition accuracy (29). The identification and characterization of internal cable insulation defects by analyzing partial discharge patterns, with signal recording and denoising using wavelet analysis and feature matrix formation with statistical operators and phase-resolved signal characteristics, achieved an accuracy band of 96 % to 92 % in the identification and characterization of the defect scale (30).

Applications in Wide Area Protection and Cybersecurity

Wide-area protection and cyber-physical security constitute an emerging front of data-driven diagnostics. The Cyber-Physical Anomaly Detection System for Wide-Area Protection, which uses measurements of synchrophasors and network packet properties to detect data integrity attacks and communication failures on measurement and control signals, combined variational modal decomposition and decision tree algorithms with rule-based decision logic, and demonstrated that the proposed algorithm outperforms existing machine learning classifiers during noisy and noise-free measurements (31). In the fault diagnosis of transmission protection systems, the algorithm based on the measurements of the phasor units of measurement detected the root cause of the failure in the protection system according to the observed state, e.g. multiple line trips and circuit breaker faults, and was improved for cases where anomalies of the data of the phased units of measurement, such as communication errors or cyberattacks, are present (5).

Trends: transfer learning and the challenges of the field

Transfer learning is the most prominent methodological trend of the period. Cross-domain fault diagnosis, which uses the knowledge transfer strategy to build models that perform well on target

tasks by leveraging knowledge of semantically related source domains but with different distributions, was first synthesized by Zheng et al. from three perspectives: research motivations, cross-domain strategies, and application objects (32). Deep transfer learning for diagnosing rotating machinery with insufficient supervised data demonstrated that data mining on different but related equipment can potentially benefit diagnostic performance on the target machine, by adversarial training of domains with different label spaces and with different failure severities (17). Domain adaptation, one of the promising solutions to the problem of generalization of diagnostic models on new machines and under new working conditions, was introduced in the context of fault diagnosis using domain adversarial neural networks along with two other popular methods, with a unified experimental protocol for fair comparison (33). Multi-scale intraclass transfer learning for bearing failure diagnosis addressed the problem of the different distribution of vibration data under changing and complex working conditions, looking for invariance between domains by reducing the distance between them (22).

In parallel, the literature has systematized persistent challenges. The review by Saufi et al. noted that the high performance of deep learning comes with challenges and costs, and discussed the potential for future work on the implementation of deep learning in fault detection and diagnosis systems (4). The review by Tang et al. identified existing challenges and possible future research orientations from deep learning-based intelligent diagnostics to rotating machinery (7), and the comparative study by Zhao et al. warned about the need for big data, data heterogeneity, and reliance on prior knowledge (6). These challenges—the scarcity of labeled data, the imbalance of classes, generalization between operating conditions and between equipment, the interpretability of deep models, and real-time deployment constitute the substrate on which the future agenda of the field is projected.

Gaps in literature

A review of the literature allows us to identify consistent gaps. First, most studies validate models in simulations or on test benches, with a relative scarcity of validations in real equipment in operation. Second, comparison between studies is difficult due to the heterogeneity of databases, experimental protocols, and performance metrics, although open-source reference studies are beginning to mitigate this problem (6). Third, the challenges of class imbalance, insufficient data, and generalization between domains are widely recognized, but solutions evaluated under industrial conditions are scarce. Fourth, the interpretability and explainability of deep models remain scarcely addressed in the literature of the period. Finally, cyber-physical frameworks that integrate data security into automated diagnostics constitute an emerging front with limited production (31).

METHOD

This research was developed as a systematic review of the literature with narrative synthesis, guided by the principles of the PRISMA 2020 standard, whose purpose was to identify, evaluate and synthesize in a structured and reproducible way the evidence published between 2019 and 2022 on the applications and trends of machine learning in the diagnosis of electrical system failures. The name systematic review responds to the strategy actually executed: structured search in databases with controlled descriptors, explicit inclusion and exclusion criteria, two-phase selection, systematic

extraction of data in matrix and synthesis by thematic analysis. No quantitative meta-analysis was performed due to the heterogeneity of the designs, application domains, algorithms and performance metrics, and the synthesis was narrative and comparative. In line with the transparency required by the PRISMA standard, the limitations of the process are explicitly stated: the protocol was not previously registered in a review platform and the selection did not use double independent review with concordance calculation, so the screening figures for each phase are presented in an aggregated manner and a formal assessment of the risk of bias with validated instruments is not reported.

The bibliographic search was directed as a priority to the Scopus and Web of Science databases, complemented with PubMed for the outcomes associated with the reliability of the equipment and with SciELO to strengthen the representation of the production in Spanish and Portuguese. Controlled descriptors in Spanish and English were used, including fault diagnosis, fault detection, fault classification, fault location, machine learning, deep learning, electrical power systems, distribution networks, transmission lines, power transformers, modular multilevel converters, high-voltage direct current, induction motors, wind turbines, photovoltaic systems, partial discharges, phasorial measurement units, fault diagnosis, fault detection, fault classification, fault location, machine learning, deep learning, convolutional neural network, long short-term memory, support vector machine, power systems, power transformers, distribution networks, transmission lines, modular multilevel converters, HVDC, induction motors, wind turbines, photovoltaic systems, partial discharge and phasor measurement units, combined with the Boolean operators AND and OR. The time window was restricted to the years 2019 to 2022, which delimits the corpus of analysis, in coherence with the purpose of the review.

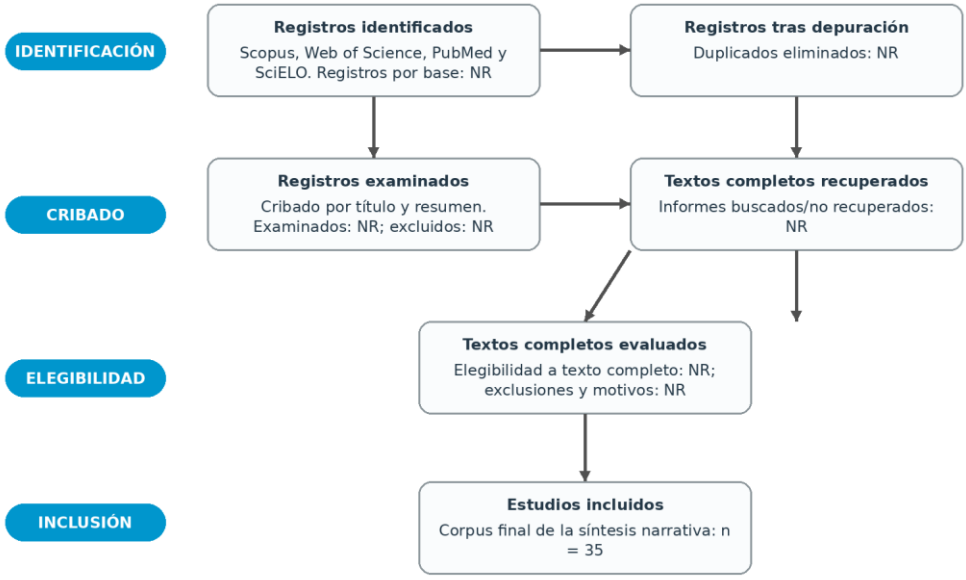
The inclusion criteria were: empirical studies and reviews focused on the application of machine learning or deep learning algorithms to the diagnosis, detection, classification or location of faults in electrical system components; research on transformers, transmission lines, distribution networks, microgrids, power electronics converters, high-voltage direct current systems, rotating electrical machines, wind turbines, photovoltaic systems, high-voltage cables and electrical insulation, or wide-area protection; studies on transfer learning and hybrid models applied to the diagnosis of electrical faults; systematic reviews, literature reviews and documentary analyses of the period; studies with availability of verifiable data or arguments; and publications in Spanish, English or Portuguese. Studies focused exclusively on mechanical machinery without an electrical component, studies on load prediction, state estimation or economic dispatch without a fault diagnosis component, conference abstracts without complete data and documents without verifiable identifier were excluded.

The selection process was carried out in two phases: a first phase of screening by title and abstract, in which the inclusion and exclusion criteria were applied, and a second phase of full-text reading to verify eligibility. After this process, the final corpus was made up of 35 publications, all of them published between 2019 and 2022 and with verifiable identifiers. Data extraction was organized in a matrix that recorded, for each document, the year, the domain of application, the study design, the algorithm or algorithmic family used, the characteristics of the data, the performance metrics reported, and the main results. The analysis was developed through thematic content analysis, which

allowed the findings to be grouped into twelve emerging categories, presented in Table 1. The synthesis was narrative and comparative, so that each category integrated the findings of the different studies and evidenced coincidences, contradictions, and gaps. The figures reported in the results correspond literally to the values published in the primary studies analyzed; This work did not collect its own empirical data, did not intervene on equipment or people, and does not generate original statistical results. As it was a review of secondary sources, the approval of a research ethics committee was not required, and maximum fidelity was sought in the transmission of the extracted data.

Figure 1.

Study selection flow according to PRISMA 2020



Note. NR/unrecorded indicates information not documented in the original revision; no quantities were estimated or invented.

RESULTS

The results presented below come exclusively from the analysis of the studies included in the review and not from empirical data collected by the authors. The final corpus consisted of 35 publications published between 2019 and 2022, whose thematic distribution is summarized in Table 1.

Table 1.

Distribution of corpus studies according to application domain and methodological family

Application Domain	Studies (n)
Machine Learning and Deep Diagnostics Overviews in Fault Diagnosis	5
Real-time transmission lines and fault location	2
Distribution networks and smart meters	3

Application Domain	Studies (n)
Microredes	1
Power transformers	6
Induction motors	3
Multi-level modular converters and HVDC systems	3
Wind turbines and condition monitoring	2
Photovoltaic systems	2
High voltage cables and partial discharges	2
Wide Area Protection and Cybersecurity	2
Transfer Learning and Mastery Adaptation	4
Total	35

Note. Prepared by the author based on the analysis of the studies included in the review. The classification responds to the main focus declared by each publication.

The analysis of the thematic distribution of the corpus reveals a mature field in the classical domains and emerging in the most recent methodological fronts. Power transformers, with 6 studies, constitute the most developed application domain, which reflects their criticality and the historical availability of dissolved gas analysis data. The general reviews, with 5 studies, show the consolidation of the field and its need for systematization. Transfer learning, with 4 studies, confirms its status as a methodological frontier. Distribution networks, induction motors and multilevel modular converters, with 3 studies each, show a balanced development, while microgrids, wind turbines, photovoltaic systems, high-voltage cables and wide-area protection, with 1 or 2 studies each, reveal fronts of recent expansion. This distribution suggests that the research has prioritized the equipment with the highest criticality and cost, and that applications to distributed and renewable generation systems constitute the growth frontier.

Table 2.

Synthesis of the main empirical studies of the corpus on the performance of machine learning in the diagnosis of electrical faults

Study and mastery	Algorithm	Reported Performance
Taha & Mansour, 2021, Transformers	Six optimized machine learning methods on dissolved gas analysis	542 samples; performance superior to conventional methods
Kherif et al., 2021, Transformers	KNN combined with the decision tree principle	501 samples; overall accuracy rate >93%
Hong et al., 2020, Transformers	Convolutional neural network over vibration images	Overall accuracy of 98.3%; more than 100 transformers in operation
Wu and Ma, 2021, wind turbines	Integrated LSTM with Kullback-Leibler divergence	94% and 92% in two turbines with different faults
Peng et al., 2019, high-voltage cables	Convolutional neural network on partial discharge patterns	Surpassed traditional pattern recognition methods

Study and mastery	Algorithm	Reported Performance
Abu-Rub et al., 2021, cable insulation	Support Vector Machines and Set Algorithms	Accuracy between 96% and 92% depending on the scale of the defect
Shao et al., 2019, induction motors	Multi-frequency deep convolutional neural network	Superior to traditional diagnostic methods
Skowron et al., 2020, induction motors	Convolutional neural network over stator current	High accuracy in incipient winding fault detection

Note. Prepared by the author based on the included studies. The values correspond to those reported by the primary sources and should not be interpreted as directly equivalent between domains.

The comparative analysis in Table 2 shows that the evidence converges in three complementary directions. First, machine and deep learning methods achieve very high levels of accuracy under controlled conditions, with values ranging from 92% to 98.3% in representative studies of the corpus, regardless of the domain of application. Second, this accuracy is obtained both with optimized surface methods, such as the support vector machine and the nearest neighbor algorithm, and with deep architectures, which indicates that the choice of algorithm depends on the nature of the data and the task rather than on the absolute superiority of an algorithmic family. Third, the predominant validation is carried out in laboratories, simulations or reference databases, with few studies deployed on real equipment in operation, such as that of Hong et al., which is the notable exception with more than 100 transformers in service. This combination of high accuracy, algorithmic plurality and predominantly controlled validation is the central finding of the review, as it delineates both the potential of machine learning and the gap between research and industrial application.

Findings according to the categories of analysis

In relation to the fundamentals, studies agree that intelligent fault diagnosis has evolved from superficial methods to deep architectures and, finally, to transfer learning, and that deep learning allows the construction of end-to-end diagnostic processes that directly link monitoring data with the health states of equipment (2). Regarding architectures, evidence documents the predominance of convolutional neural networks, valued for their ability to learn features directly from raw data and for the reduction of parameters through shared weight, and recurrent networks with long-term memory, valued for their ability to process the temporal dimension of signals (9,10). In transformers, studies show that dissolved gas analysis is the predominant input, with nonlinear support vector machine and array methods as the most appropriate classifiers, and that vibration emerges as a low-cost, non-intrusive alternative with accuracy greater than 98% (14). In distribution lines and networks, evidence documents real-time localization using convolutional networks with data from phasor measurement units (17) and the use of data from smart meters and phasor micro measurement units for fault classification and localization (18,19,20). In microgrids, smart sensing systems based on local measurements eliminate reliance on robust communication infrastructure (21). In modular multilevel converters, deep methods and hybrid models demonstrate robustness and accuracy in diagnosing open-loop faults (23,9,22). In rotating machines, convolutional networks applied to currents and vibrations achieve high accuracy in the incipient detection of winding faults. In renewable systems, wind turbine condition monitoring using hybrid models achieves accuracies of 94 % and 92 % (10),

and reviews on PV systems document the power loss of 18.9 % attributable to faults and the consolidation of deep methods for their diagnosis (28). In electrical insulation, deep recognition of partial discharge patterns exceeds traditional methods (29), with accuracies between 96 % and 92 % in the characterization of defects (30). In wide-area protection, cyber-physical anomaly detection systems outperform existing classifiers (31). Finally, transfer learning is the dominant trend to overcome the obstacles of scarcity of labeled data and generalization across domains (17,34). Complementary adaptation reviews and studies reinforce this trend (32,35).

DISCUSSION

The discussion of the findings allows us to identify substantial coincidences between the studies reviewed. There is consensus that machine learning, and in particular deep learning, is the dominant paradigm for diagnosing faults in electrical systems, with very high levels of accuracy in the most developed application domains, and that this superiority is explained by the ability of deep models to learn hierarchical representations directly from the data, eliminating the dependence on manual feature extraction (2,4). This convergence crosses transformers, lines, distribution networks, converters, rotating machines, and renewable systems, and is supported by designs that range from experimental study on test benches to field studies with equipment in operation, which gives effectiveness the status of the most robust finding of the review.

Divergences emerge, however, in the interpretation of the relative weight of algorithmic families. While syntheses dedicated to convolutional networks highlight their structural advantage in the processing of nonlinear signals and displacement-dependent data, applications based on long-term memory emphasize the temporal dimension of diagnosis (10), and studies on dissolved gas analysis show that optimized surface methods, such as the nonlinear support vector machine and ensemble methods, remain highly competitive (11,12). This apparent contradiction admits of a complementary reading: the superiority of an algorithmic family depends on the nature of the data, the size of the signal, the availability of samples, and the diagnostic task, and the evidence from the period does not support the idea of a universally dominant architecture. The open-source reference study by Zhao et al., by evaluating deep algorithms in a comparative and reproducible manner, constitutes a decisive step towards empirical resolution of this question (6).

A second axis of discussion concerns the gap between experimental accuracy and industrial applicability. Corpus studies achieve remarkable precisions, but most validate models in simulations, in laboratories or in reference databases, and only exceptionally in real equipment in operation (14). This gap is explained by several converging factors: the limited availability of labeled data on real faults, the rarefaction of incipient faults, the imbalance of classes, the variability of operating conditions, and the costs of monitoring instrumentation. The review by Saufi et al. systematized these challenges and warned that the high performance of deep learning is accompanied by challenges and costs that condition its implementation (4), and the review by Tang et al. projected them towards future orientations of intelligent diagnosis of rotating machinery (7). On the electrical level, these challenges take on an additional dimension: data security and the integration of expert knowledge

with artificial intelligence appear as essential directions for the future development of fault diagnosis in smart grids, together with the cybersecurity of wide-area protection systems (31).

A third axis of discussion concerns transfer learning as a structural response to data challenges. Evidence from the period shows that cross-domain diagnosis, which transfers knowledge from semantically related source domains but with different distributions, is the most promising strategy to overcome the scarcity of labeled data and the lack of generalization between equipment and operating conditions (32). Empirical studies demonstrate the feasibility of transferring diagnostic knowledge between related machines with different label spaces (17), the applicability of domain adversarial adaptation in realistic diagnostic scenarios (33), and the effectiveness of multiscale intraclass transfer learning for bearing failures under changing working conditions (22). This methodological convergence suggests that the frontier of the field has shifted from model architecture to data and domain management, and that future research should prioritize standardized evaluation protocols, open reference databases, and fair comparison frameworks, along the lines of the study by Zhao et al. (6).

A fourth axis of discussion concerns the distribution of production by domains. The concentration of research on power transformers is consistent with their economic criticality and the maturity of their diagnostic instrumentation, while the lower production in microgrids, renewable systems, and wide-area protection reflects both the youth of these domains and the complexity of their fault conditions, characterized by the variability of distributed generators and the stochasticity of fault characteristics (20). This asymmetry implies that the solutions developed for mature domains are not directly transferable to emerging domains, and that the generation of specific evidence is a requirement of the energy transition. The implications for practice and research are considerable: the reviewed evidence supports the gradual incorporation of learning-based diagnostic systems into the asset management of utilities, starting with the most critical equipment and with validation in real conditions; the adoption of deep architectures when data availability allows and optimized surface methods when data is scarce; investment in the measurement infrastructure – phased measurement units, micro units, smart meters – that feeds diagnostic models; and the integration of cybersecurity considerations into the design of automated diagnostic systems (31).

Among the limitations of this review, the heterogeneity of the designs, databases, experimental protocols, and metrics should be recognized, which prevented quantitative synthesis and limits the direct comparability of performances; the predominance of validation in simulations and in laboratories, which conditions generalization to real equipment; the absence of a formal assessment of risk of bias and a double independent review, typical of systematic reviews with a registered protocol; the restriction of the time window to the years 2019 to 2022, which excludes subsequent developments; and the possible omission of relevant studies published in languages other than Spanish, English, and Portuguese or in gray literature. These limitations do not invalidate the findings, but they recommend caution in generalizing the conclusions.

Research gaps outline a clear future agenda: validation studies are required on actual electrical equipment in operation, with incipient fault data and variable operating conditions; standardized

evaluation protocols and open reference databases that allow fair comparison of algorithms; research on class imbalance and the scarcity of labeled data in the electrical field; the development of interpretable and explainable methods that integrate the expert knowledge of operators; the expansion of evidence into microgrids, distributed and renewable generation systems, and wide-area protection; and the design of cyber-physical frameworks that ensure data integrity against attacks and communication errors.

CONCLUSIONS

In relation to the general objective, the review confirms that power transformers, transmission lines and distribution networks concentrated a substantial part of machine learning applications for fault diagnosis between 2019 and 2022. In parallel, power electronics converters, rotating electrical machines, wind and photovoltaic systems and high-voltage insulation expanded the scope of the field, evidencing a progressive diversification towards electrical assets and scenarios of greater operational complexity.

The evidence examined shows a clear methodological transition from superficial classifiers, such as support vector machines and artificial neural networks, to deep architectures, especially CNN, RNN/LSTM and transfer learning strategies. However, optimized conventional methods continue to be relevant when datasets are small, structured, or require greater interpretability. Therefore, the results do not support the existence of a universally superior architecture, but rather a selection dependent on the domain, the signal, and the diagnostic task.

The high accuracies reported by several studies demonstrate the technical potential of machine learning, but they must be interpreted within the specific conditions of each experiment. The heterogeneity of datasets, signal types, metrics, validation protocols, and operating conditions makes it impossible to directly compare performance percentages across domains. This methodological diversity also justifies the absence of quantitative meta-analysis and reinforces the need for standardized protocols that allow for reproducible, transparent, and technically valid comparisons between algorithms.

The main gap identified for industrial adoption corresponds to the distance between the high performance obtained in simulations, laboratories or baselines and sustained validation in real electrical equipment. A secure implementation requires representative data of rare and incipient failures, external validation, robustness analysis against operational changes, explainability of decisions and cybersecurity mechanisms. It is also essential to strengthen data governance and the integration of expert knowledge during the design and evaluation of diagnostic systems.

From a methodological perspective, future updates of this review should pre-register the protocol, extend the search to specialized engineering databases such as IEEE Xplore, apply double independent review, and fully document each stage of the PRISMA flow. They should also incorporate formal quality or risk of bias assessment tools and explicit strategies to manage heterogeneity. These improvements would increase the reproducibility, traceability, and robustness of the available

evidence and facilitate its responsible use in decisions about maintenance, protection, and management of electrical assets.

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ETHICAL CONSIDERATIONS

Not applicable. This study is a review of published literature and did not involve direct participation of human beings, animals, interventions, or collection of identifiable personal data.

ARTIFICIAL INTELLIGENCE (AI) USE STATEMENT

The authors declare that the generative artificial intelligence tool ChatGPT (OpenAI) was used exclusively to support the organization of the article and translation of text. Its use did not determine the scientific content, study design, source selection, data analysis, interpretation of results, or conclusions. Full responsibility for the content remains with the authors.

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The authors declare no conflicts of interest.

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